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**Artificial Intelligence (AI) In ICT Management and Performance of
Commercial Banks in Nairobi City County, Kenya**



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Artificial Intelligence (AI) In ICT Management and Performance of Commercial Banks in Nairobi City County, Kenya

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ABSTRACT

Purpose: The general objective of the study is to assess the effect of artificial intelligence (AI) in ICT management on performance of commercial banks in Nairobi City County, Kenya. Specifically, the study sought to establish the influence of machine learning and natural language processing on performance of commercial banks in Nairobi City County.

Methodology: The descriptive research design was employed. The unit of analysis for the study was 40 commercial banks in Kenya (CBK, 2024) while the unit of observation was management employees. The accessible population was 246 individuals comprising of 41 top managers, 82 middle level managers and 123 lower-level managers. The study used Krejcie and Morgan (1970) formula to arrive at the sample size. The study sample size was therefore 152 employees. Stratified random sampling was applied to get the respondents. Data was collected using a self-administered semi-structured questionnaire. Data obtained from the field was coded, cleaned, and entered into the computer for analysis using the SPSS version 25. Inferential statistical analysis used was multiple regression and correlation analysis.

Findings: The study found that machine learning has a positive and significant effect on performance of commercial banks in Nairobi City County, Kenya. In addition, the study showed that natural language processing has a positive and significant effect on performance of commercial banks in Nairobi City County, Kenya.

Unique Contribution to Theory, Practice and Policy: Based on the findings, the study recommends that commercial banks in Kenya should invest in the adoption and integration NLP technologies to enhance customer engagement and operational efficiency. By deploying NLP-powered tools such as chatbots, automated customer support systems, and sentiment analysis platforms, banks can provide faster, more accurate, and personalized responses to customer inquiries while reducing service costs.

Key Words: *Artificial Intelligence (AI) In ICT Management, Machine Learning, Natural Language Processing, Commercial Banks*

Background of the Study

Artificial Intelligence (AI) has become a transformative force in the global financial sector, particularly in enhancing ICT (Information and Communication Technology) management practices (Adebayo & Akinyemi, 2022). Globally, banks and financial institutions are leveraging AI technologies such as machine learning, robotic process automation (RPA), expert systems, and natural language processing (NLP) to optimize service delivery, reduce operational costs, and strengthen cybersecurity (Zeng, Lu, & Huangfu, 2022). According to a 2023 McKinsey report, AI adoption in banking has the potential to generate up to \$1 trillion in additional value annually, largely through productivity gains and cost reduction. The World Economic Forum (2022) noted that over 80% of global financial institutions had either deployed or piloted AI solutions, with a focus on risk management, fraud detection, and customer service automation.

In the realm of ICT management, AI plays a crucial role in streamlining system monitoring, predictive maintenance, IT infrastructure optimization, and managing large datasets for decision-making. For example, AI-powered chatbots and virtual assistants now handle over 75% of routine banking inquiries worldwide, reducing human resource burdens and enhancing customer satisfaction (IBM Global AI Adoption Index, 2023). Furthermore, financial institutions are using AI to strengthen cybersecurity frameworks, detect anomalies in real-time, and respond swiftly to emerging threats. These AI applications are significantly transforming traditional ICT management into intelligent, adaptive, and cost-effective operations, with direct implications for overall organizational performance.

In commercial banking, particularly in developing economies, AI adoption is increasingly recognized as a strategic necessity for competitiveness and innovation. Banks that integrate AI into their ICT management frameworks experience enhanced efficiency in back-office operations, improved accuracy in credit scoring, and more personalized customer experiences. A Deloitte (2022) global survey of financial institutions revealed that banks using AI in ICT processes reported a 30–40% improvement in operational performance metrics. As banks strive to meet rising customer expectations and regulatory demands, AI-driven ICT management stands out as a critical enabler of financial inclusion, operational excellence, and long-term performance sustainability.

Commercial banks in Nairobi City County, Kenya, play a central role in the country's financial ecosystem. As the capital and economic hub of Kenya, Nairobi hosts the headquarters and major branches of most commercial banks operating in the country (Nkanata & Maina, 2025). These banks provide a wide range of financial services including personal and business banking, loans and credit facilities, savings and investment options, foreign exchange, and mobile and digital banking services (Kimutai & Muchelule, 2025). Their presence supports not only individuals and businesses in Nairobi but also acts as a gateway to banking services for customers across Kenya and the East African region. Nairobi's commercial banks are regulated by the Central Bank of

Kenya (CBK), which ensures they operate under sound financial and regulatory frameworks (Munga, 2024). The city is home to both large local banks such as KCB Bank, Equity Bank, and Co-operative Bank of Kenya, as well as international banks like Standard Chartered, Citibank, and Absa Bank Kenya (Nkanata & Maina, 2025). These banks compete and collaborate within a dynamic financial environment, driving innovation—especially in mobile and digital banking technologies. Nairobi, being the tech center of East Africa, has seen rapid adoption of digital banking services, which has further expanded access to financial services for its population (Kimutai & Muchelule, 2025).

Furthermore, commercial banks in Nairobi contribute significantly to economic development by financing key sectors such as real estate, trade, manufacturing, and agriculture (Munga, 2024). They also play a vital role in promoting financial inclusion by offering tailored products for small and medium-sized enterprises (SMEs), youth, and low-income earners. With continuous growth in the fintech sector and support from the government for financial innovation, Nairobi's commercial banking sector is positioned to continue evolving as a key driver of Kenya's economic growth (Nkanata & Maina, 2025).

Statement of the Problem

The performance of commercial banks in Kenya remains a critical concern in the face of rising customer expectations, increased competition, cybersecurity threats, and operational inefficiencies. While Artificial Intelligence (AI) presents transformative potential for enhancing ICT management—through automation, predictive analytics, intelligent decision-making, and improved service delivery—its adoption within Kenya's banking sector has been uneven and limited in scale. Many banks continue to rely on legacy systems that lack real-time responsiveness, scalability, and adequate security features, hindering their ability to operate efficiently in the modern digital economy (CBK, 2022).

Despite Kenya being recognized as a regional leader in fintech innovation, the integration of AI in ICT functions such as infrastructure management, customer support systems, fraud detection, and cybersecurity remains relatively low. The Central Bank of Kenya (CBK), in its 2023 industry report, highlighted that only 47% of commercial banks had adopted AI-powered ICT tools. These include chatbots for customer engagement, machine learning algorithms for risk assessment and credit scoring, and intelligent analytics for business forecasting and decision support. This means that over half of the sector still relies on traditional systems that are often reactive rather than proactive—unable to leverage real-time data for rapid decision-making or predictive maintenance of ICT infrastructure. The slow uptake is especially pronounced among mid-tier and small banks, which often cite high implementation costs, lack of technical expertise, and uncertain return on investment as major barriers (KNBS, 2024).

Moreover, the issue extends to cybersecurity, where AI can play a vital role in real-time threat detection, anomaly detection, and automated response to cyber incidents. However, a 2022 study

by the Communications Authority of Kenya (CAK) found that only 39% of financial institutions had deployed AI-based cybersecurity frameworks. This limited investment increases exposure to cyber risks, particularly as financial services become more digital and data-driven. The shortfall is alarming in light of rising cases of cyber fraud and phishing attacks targeting banking systems. As the frequency and complexity of cyber threats evolve, AI-enabled security tools are no longer optional but essential to safeguard customer data and ensure compliance with regulatory standards. In addition, operational inefficiencies continue to undermine performance across the sector. The Kenya Institute for Public Policy Research and Analysis (KIPPRA, 2022) reported that ICT-related inefficiencies—such as system downtimes, slow response times, and fragmented data systems—account for up to 30% of service delivery delays in commercial banks. These inefficiencies can lead to customer dissatisfaction, higher operational costs, and reduced competitiveness. The lack of intelligent automation in ICT management means that many routine tasks still require manual intervention, slowing down internal processes and reducing scalability. In sum, the limited integration of AI in ICT management not only hampers operational performance but also exposes banks to heightened risks and lost opportunities for innovation, growth, and enhanced service delivery.

While leading banks such as Equity Bank and KCB have made strides in integrating AI for digital banking and fraud detection, smaller and mid-tier banks face barriers including high implementation costs, limited technical expertise, and data integration challenges. These disparities raise concerns about the overall impact of AI on the sector's performance and competitiveness (KNBS, 2024). As the global banking environment becomes increasingly digitized, a lack of comprehensive adoption of AI in ICT management may undermine Kenyan banks' ability to scale operations, enhance customer satisfaction, reduce operational costs, and ensure regulatory compliance (CAK, 2024). This study therefore sought to assess the effect of AI in ICT management on the performance of commercial banks in Nairobi City County, Kenya

Objectives of the Study

General Objective

The general objective of the study is to assess the effect of artificial intelligence (AI) in ICT management on performance of commercial banks in Nairobi City County, Kenya

Specific Objectives

- i. To establish the influence of machine learning on performance of commercial banks in Nairobi City County, Kenya
- ii. To examine the influence of natural language processing on performance of commercial banks in Nairobi City County, Kenya

Theoretical Review

Technological Determinism Theory

Technological Determinism Theory developed by Marshall McLuhan (1964) is a concept in communication and social sciences that emphasizes the powerful influence of technology on society, culture, and human behavior (Feng, Kephart & Juarez-Colunga, 2021). The theory argues that technological innovations are the main driving force behind social change and development (Chimbunde, Sigwadhi & Tamuzi, 2023). According to this perspective, once a new technology is introduced, it reshapes how people interact, communicate, work, and live, often in ways that cannot be easily controlled or reversed. Essentially, technology is seen as an autonomous factor that dictates the pace and direction of human progress (Mwangi, 2024).

A central idea of technological determinism is that technology shapes society rather than society shaping technology. This suggests that inventions such as the printing press, the telephone, or the internet did not just emerge in response to human needs, but rather created new possibilities and behaviors that transformed societies (Friedman, Mwangi & Muthoka, 2025). For instance, the rise of the internet and social media has redefined communication, business models, politics, and even personal relationships, illustrating how technology can alter the structures and dynamics of daily life. The theory has both optimistic and critical dimensions (Kagendi & Mwau, 2023). On one hand, it can be seen as progressive, showing how technological advancements drive innovation, efficiency, and human development (Feng, Kephart & Juarez-Colunga, 2021). On the other hand, critics argue that technological determinism overlooks human agency, cultural values, and social contexts in shaping the adoption and use of technology. They stress that while technology influences society, it is also shaped by human decisions, policies, and needs (Chimbunde, Sigwadhi & Tamuzi, 2023). This theory was used to establish the influence of machine learning on performance of commercial banks in Nairobi City County, Kenya.

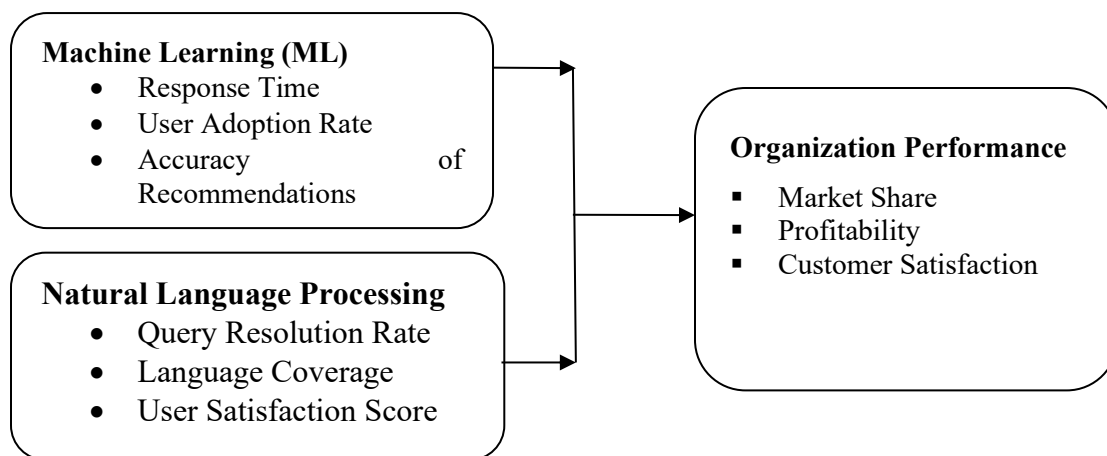
Diffusion of Innovations Theory

The Diffusion of Innovations Theory explains how new ideas, products, or practices spread within a social system over time. Developed by Everett Rogers (1962), the theory focuses on the process through which an innovation is communicated and adopted by members of a community or organization (Katsuki, Narita & Matsumori, 2020). It highlights that the spread of an innovation is not instantaneous but occurs gradually as people learn about it, evaluate its benefits, and decide whether or not to incorporate it into their lives or work (Lester, Manson & Semakula, 2025). Central to the theory are five categories of adopters based on their willingness to embrace an innovation: innovators, early adopters, early majority, late majority, and laggards. Innovators are the first to try new ideas, often taking risks, while early adopters tend to be opinion leaders who help influence others (Pair, Vicas & Weber, 2021). The early and late majority make up the bulk of adopters, adopting innovations after seeing evidence of success, and laggards are the last, typically resistant to change and adopting only when necessary.

Understanding these categories helps organizations and marketers target their efforts effectively (Kituku, Nganga & Muchemi, 2021).

The theory also emphasizes five key factors influencing the adoption rate of an innovation: relative advantage (how much better the innovation is compared to current options), compatibility (how well it fits with existing values and practices), complexity (how difficult it is to understand or use), trialability (the opportunity to test it before full adoption), and observability (how visible the results are to others) (Sauer, Overos & Newlands, 2022). Innovations that score well on these factors tend to spread more quickly. Diffusion of Innovations Theory provides valuable insight into how change occurs in societies and how to facilitate the successful uptake of new ideas (Katsuki, Narita & Matsumori, 2020). This theory is relevant in examining the influence of natural language processing on performance of commercial banks in Nairobi City County, Kenya.

Conceptual Framework



Independent variables

Dependent variable

Figure 1: Conceptual framework

Empirical Review

Machine Learning (ML) and Organization Performance

Feng, Kephart and Juarez-Colunga (2021) conducted a study on the effect of predicting COVID-19 mortality risk in Toronto, Canada: a comparison of tree-based and regression-based machine learning methods. The study compared the performance of classification tree, random forest, extreme gradient boosting, logistic regression, generalized additive model and linear discriminant analysis to predict the mortality risk among 49,216 COVID-19 positive cases in Toronto, Canada, reported from March 1 to December 10, 2020. The study found XGBoost is highly discriminative and has superior performance over conventional tree-based methods.

Regression-based methods had comparable performance to the XGBoost with slightly lower AUCs and higher Brier's scores. The study concluded that XGBoost offers superior performance over conventional tree-based methods and minor improvement over regression-based methods for predicting COVID-19 mortality risk in the study population.

Chimbunde, Sigwadhi and Tamuzi (2023) conducted a study on the effect of machine learning algorithms for predicting determinants of COVID-19 mortality in South Africa. Data for this study were obtained from 392 COVID-19 ICU patients enrolled. The study found that from the semi-parametric logistic regression and ANN variable importance, age, gender, cluster, presence of severe symptoms, being on the ventilator, and comorbidities of asthma significantly contributed to ICU death. Based on the findings, we can conclude that both ANN and RF can predict COVID-19 mortality in the ICU with accuracy

Mwangi (2024) conducted a study on the effect of analyzing the role of artificial intelligence and machine learning in optimizing supply chain processes in Kenya. This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low cost advantage as compared to a field research. The study found that Artificial intelligence (AI) and machine learning (ML) play a pivotal role in optimizing supply chain processes by enhancing demand forecasting accuracy through sophisticated algorithms. The study concluded that the role of artificial intelligence (AI) and machine learning (ML) in optimizing supply chain processes is increasingly recognized as a game-changer in the field of supply chain management.

Friedman, Mwangi and Muthoka (2025) conducted a study on the effect of machine learning to improve HIV screening using routine data in Kenya. The study combined de-identified individual-level EMR data from 167,509 individuals without a previous HIV diagnosis who were tested between June and November 2022. The study included demographics, clinical histories and HIV-relevant behavioral practices with open-source data that describes population-level behavioral practices as other variables in the model. The study found that all model types demonstrated predictive performance on the test set with AUCPR that exceeded the current positivity rate. XGBoost generated the greatest AUCPR, 10.5 times greater than the rate of positive test results. The study concluded that machine learning applied to routine HIV testing data may be used as a clinical decision support tool to refer persons for HIV testing.

Kagendi and Mwau (2023) conducted a study on the effect of machine learning approach to predict HIV viral load hotspots in Kenya using real-world data. A random forest model was built to predict the hotspot status of a health facility in the upcoming month, starting from 2016. The study found that the model discriminates hotspots from non-hotspots with an accuracy of 78%. The F1 score of the model is 69% and the Brier score is 0.139. The study concluded that the hotspot mapping model can be essential to antiretroviral therapy programs

Natural Language Processing and Organization Performance

Katsuki, Narita and Matsumori (2020) conducted a study on the effect of preliminary development of a deep learning-based automated primary headache diagnosis model using Japanese natural language processing of medical questionnaire. The study retrospectively investigated our primary headache database and developed a diagnosis model using the DL framework (Prediction One, Sony Network Communications Inc., Japan). The study used age, sex, date, and embedding layer made by the medical questionnaire's natural language processing (NLP). The study found that eight hundred and forty-eight primary headache patients (495 women and 353 men) are included. The study concluded that the DL-based diagnosis model for primary headaches using the raw medical questionnaire's Japanese NLP would be useful in performing efficient medical practice after ruling out the secondary headaches.

Lester, Manson and Semakula (2025) conducted a study on the effect of natural language processing to evaluate texting conversations between patients and healthcare providers during COVID-19 Home-based Care in Rwanda at scale. The study aimed to assess the texting patterns and communicated topics to better understand patient experiences. The study found that topic classification revealed that medical topics, such as symptoms, diagnostics, prevention, and treatment, were commonly discussed, reflecting patients' primary focus on their health status and obtaining medical guidance. The study concluded that moving forward, future research should explore ways to further optimize the evaluation of text-based communication for greater insights into the patient care journey in pandemics, and clinical care

Pair, Vicas and Weber (2021) conducted a study on the effect of quantification of gender bias and sentiment toward political leaders over 20 years of Kenyan news using natural language processing. The study measured gender bias in these embedding's and used sentiment analysis to predict quantitative sentiment scores for sentences surrounding female leader names compared to male leader names. The study found that bias in leadership words for men and women measured from Daily Nation word embedding's corresponded to temporal trends in men and women's participation in political leadership (i.e., parliamentary seats) using Glove and word2vec algorithms. The study concluded that natural language processing is a powerful method for gaining insights into and quantifying trends in gender biases and sentiment in news media.

Kituku, Nganga and Muchemi (2021) conducted a study on the effect of leveraging on cross linguistic similarities to reduce grammar development effort for the under-resourced languages: a case of Kenyan Bantu languages. The shared grammar was developed using the morphology-driven approach, where the lexicons are defined first, followed by inflection regular expression and finally the syntax production rules. The resulting congruent Bantu parameterized grammar had share ability for category linearization's, parameters, paradigms, and syntax rules, while portability (modification) was exhibited in paradigms, parameter plus syntax rules. The research concludes leveraging on the cross linguistic similarities of principles and parameters

significantly reduces multilingual grammar's development effort and contributes by developing the Bantu parameterized grammar which demonstrates how the effort of developing the rule base has been significantly reduced in languages where data is a scarce commodity.

Sauer, Overos and Newlands (2022) conducted a study on the effect of analyzing multilingual discussions of the standard gauge railway project in Kenya using natural language processing and social media analysis. The study used automated natural language processing strategies as well as manual analysis of social media data from Twitter to understand discussion topics, attitudes, and sentiments of Kenyans towards domestic Kenya-China infrastructure projects. The study found that the BRI may be a new type of international development strategy that challenges Western conceptions of international cooperation. The study concluded that online media remains an important venue for gleaning information about public discussion of international relations

RESEARCH METHODOLOGY

The descriptive research design was employed where data was collected one point in time. Creswell and Creswell (2019) notes that a descriptive survey seeks to obtain information that describes existing phenomena by asking questions relating to individual perceptions and attitudes. The unit of analysis for the study was 40 commercial banks in Kenya (CBK, 2024) while the unit of observation was management employees. The accessible population was 246 individuals comprising of 41 top managers, 82 middle level managers and 123 lower-level managers as shown in Table 1.

Table 1: Target Population

Category	Target Population
Top level Managers	41
Middle Level managers	82
Lower-Level Managers	123
Total	246

Source: Commercial Banks (2024)

The study used Krejcie and Morgan (1970) formula to arrive at the sample size. The selection formula was as follows:

$$n = \frac{N}{1 + (N-1)e^2}$$

Where n= the required sample size

N = is the Target Population (246)

e = accuracy level required. Standard error = 5%

Sample calculation

$$n = \frac{246}{1 + (246)0.05^2}$$

$$n = 152.32$$

n=152 respondents

Data was collected using a self-administered semi-structured questionnaire. Semi-structured questionnaires were used since they enable the researcher collect quantitative data. A pilot test was conducted to determine validity and reliability of the data collection instrument. The responses from respondents were used to adjust and refine questionnaire accordingly. According to Mugenda and Mugenda (2019) the pretest sample should be between 1% and 10% depending on the sample size. The study used 10% of the sample size (15 respondents) to do the pilot study

Data obtained from the field was coded, cleaned, and entered into the computer for analysis using the SPSS version 25. Presentation of data was done in form of quantitative and qualitative reports which were presented in forms of tables and essay. For the quantitative reports, the tables consisted of mean and standard deviation values that were used to make interpretation of the analysis. Descriptive statistical included frequency, percentages, mean and standard deviation. Inferential statistical analysis used was multiple regression and correlation analysis. The significant of each independent variable was tested at a confidence level of 95%. The multiple regression model was as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

Where;

Y = dependent variable (Performance of commercial banks in Nairobi City County, Kenya)

X₁ = Machine learning

X₂ = Natural language processing

β₀ = the constant term

β₁₋₂ = the Beta coefficient

ε = the error term

PRESENTATION, ANALYSIS AND INTERPRETATION OF DATA

Response Rate

The researcher sampled 152 respondents who were each administered with the questionnaires. From the 152 questionnaires 132 were completely filled and returned hence a response rate of 86.8%. The response rate was considered as suitable for making inferences from the data collected. As indicated by Metsamuuronen (2019), a response rate that is above fifty percent is considered adequate for data analysis and reporting while a response rate that is above 70% is

classified as excellent. Hence, the response rate of this study was within the acceptable limits for drawing conclusions and making recommendations.

Descriptive Statistics

Machine Learning and Organization Performance

The first specific objective of the study was to establish the influence of machine learning on performance of commercial banks in Nairobi City County, Kenya. The respondents were requested to indicate their level of agreement on various statements related to machine learning and performance of commercial banks in Nairobi City County, Kenya. The results were as shown Table 2.

From the results, the respondents agreed that the machine learning system provides results in a timely and efficient manner (M= 3.867, SD= 0.761). In addition, the respondents agreed that response time of the ML system is fast enough to support real-time decision-making (M=3.841, SD=0.864). Further, the respondents agreed that the interface and usability of the ML system encourage regular use by employees (M=3.784, SD=0.772).

From the results, the respondents agreed that training and support resources contribute to the high adoption rate of the ML system (M=3.755, SD=0.596). In addition, the respondents agreed that the ML system consistently provides recommendations that align with actual outcomes (M=3.711, SD=0.783). Further, the respondents agreed that the system improves its accuracy over time through continuous learning and updates (M=3.691, SD=0.801).

Table 2: Machine Learning and Organization Performance

Statements	Mean	Std. Deviation
The machine learning system provides results in a timely and efficient manner.	3.867	0.761
Response time of the ML system is fast enough to support real-time decision-making.	3.841	0.864
The interface and usability of the ML system encourage regular use by employees.	3.784	0.772
Training and support resources contribute to the high adoption rate of the ML system.	3.755	0.596
The ML system consistently provides recommendations that align with actual outcomes.	3.711	0.783
The system improves its accuracy over time through continuous learning and updates.	3.691	0.801
Aggregate	3.775	0.763

Natural Language Processing and Organization Performance

The second specific objective of the study was to examine the influence of natural language processing on performance of commercial banks in Nairobi City County, Kenya. The respondents were requested to indicate their level of agreement on various statements related to natural language processing and performance of commercial banks in Nairobi City County, Kenya. The results were as shown Table 3.

From the results, the respondents agreed that the accuracy of query interpretation by the NLP system meets our performance expectations (M= 3.899, SD= 0.785). In addition, the respondents agreed that the system consistently provides relevant and helpful responses to user inputs (M=3.886, SD=0.643). Further, the respondents agreed that language support provided by the NLP system aligns well with customer demographics (M=3.808, SD=0.705).

From the results, the respondents agreed that users are able to communicate effectively with the system in their preferred language (M=3.764, SD=0.582). In addition, the respondents agreed that users report a high level of satisfaction with the quality of interaction with the NLP system (M=3.736, SD=0.641). Further, the respondents agreed that the implementation of NLP positively impacts the overall user experience (M=3.710, SD=0.889).

Table 3: Natural Language Processing and Organization Performance

Statements	Mean	Std. Deviation
The accuracy of query interpretation by the NLP system meets our performance expectations.	3.899	0.785
The system consistently provides relevant and helpful responses to user inputs.	3.886	0.643
Language support provided by the NLP system aligns well with customer demographics.	3.808	0.705
Users are able to communicate effectively with the system in their preferred language.	3.764	0.582
Users report a high level of satisfaction with the quality of interaction with the NLP system.	3.736	0.641
The implementation of NLP positively impacts the overall user experience.	3.710	0.889
Aggregate	3.801	0.707

Organization Performance

The respondents were requested to indicate their level of agreement on various statements related to performance of commercial banks in Nairobi City County, Kenya. The results were as shown Table 4.

From the results, the respondents agreed that they effectively expand their customer base in both existing and new markets (M= 3.791, SD= 0.581). In addition, the respondents agreed that their bank is perceived as a market leader in the financial services sector (M=3.764, SD=0.762). Further, the respondents agreed that operational efficiency significantly contributes to their overall profitability (M=3.731, SD=0.708).

From the results, the respondents agreed that their product and service offerings are well-aligned with revenue-generating opportunities (M=3.718, SD=0.848). In addition, the respondents agreed that their bank regularly receives positive feedback from customers about their services (M=3.699, SD=0.792). Further, the respondents agreed that they have effective systems in place to address and resolve customer complaints promptly (M=3.650, SD=0.632).

Table 4: Organization Performance

Statements	Mean	Std. Deviation
We effectively expand our customer base in both existing and new markets.	3.791	0.581
Our bank is perceived as a market leader in the financial services sector.	3.764	0.762
Operational efficiency significantly contributes to our overall profitability.	3.731	0.708
Our product and service offerings are well-aligned with revenue-generating opportunities.	3.718	0.848
Our bank regularly receives positive feedback from customers about our services.	3.699	0.792
We have effective systems in place to address and resolve customer complaints promptly.	3.650	0.632
Aggregate	3.726	0.721

Inferential Statistics

Inferential statistics such as correlation analysis and regression analysis were used to assess the relationships between the independent variables (machine learning and natural language processing) and the dependent variable (performance of commercial banks in Nairobi City County, Kenya).

Correlation Analysis

This research adopted Pearson correlation analysis determine how the dependent variable (performance of commercial banks in Nairobi City County, Kenya) relates with the independent variables (machine learning and natural language processing).

Table 5: Correlation Coefficients

		Organization Performance	Machine Learning	Natural Language Processing
Organization Performance	Pearson Correlation	1		
	Sig. (2-tailed)			
	N	132		
Machine Learning	Pearson Correlation	.868**	1	
	Sig. (2-tailed)	.001		
	N	132	132	
Natural Language Processing	Pearson Correlation	.880**	.117	1
	Sig. (2-tailed)	.000	.063	
	N	132	132	132

** . Correlation is significant at the 0.01 level (2-tailed).

From the results, there was a very strong relationship between machine learning and performance of commercial banks in Nairobi City County, Kenya ($r = 0.868$, p value =0.001). The relationship was significant since the p value 0.001 was less than 0.05 (significant level). The findings are in line with the findings of Feng, Kephart and Juarez-Colunga (2021) who indicated that there is a very strong relationship between machine learning and organization performance.

Moreover, there was a very strong relationship between natural language processing and performance of commercial banks in Nairobi City County, Kenya ($r = 0.880$, p value =0.000). The relationship was significant since the p value 0.000 was less than 0.05 (significant level). The findings are in line with the findings of Lester, Manson and Semakula (2025) who indicated that there is a very strong relationship between natural language processing and organization performance.

Regression Analysis

Multivariate regression analysis was used to assess the relationship between independent variables (machine learning and natural language processing) and the dependent variable (performance of commercial banks in Nairobi City County, Kenya).

Table 6: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.834 ^a	.695	.694	.10381

a. Predictors: (Constant), machine learning and natural language processing

The model summary was used to explain the variation in the dependent variable that could be explained by the independent variables. The r-squared for the relationship between the independent variables and the dependent variable was 0.695. This implied that 69.5% of the

variation in the dependent variable (performance of commercial banks in Nairobi City County, Kenya) could be explained by independent variables (machine learning and natural language processing).

Table 7: Analysis of Variance

Model	Sum of Squares	Df	Mean Square	F	Sig.
Regression	102.061	2	51.031	147.063	.002 ^b
1 Residual	44.741	129	.347		
Total	146.802	131			

a. Dependent Variable: performance of commercial banks in Nairobi City County, Kenya

b. Predictors: (Constant), machine learning and natural language processing

The ANOVA was used to determine whether the model was a good fit for the data. F calculated was 147.063 while the F critical was 3.066. The p value was 0.002. Since the F-calculated was greater than the F-critical and the p value 0.002 was less than 0.05, the model was considered as a good fit for the data. Therefore, the model can be used to predict the influence of machine learning and natural language processing on performance of commercial banks in Nairobi City County, Kenya.

Table 8: Regression Coefficients

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	0.274	0.072		3.806	0.000
machine learning	0.357	0.093	0.358	3.839	0.001
natural language processing	0.369	0.098	0.368	3.765	0.000

a Dependent Variable: performance of commercial banks in Nairobi City County, Kenya

The regression model was as follows:

$$Y = 0.274 + 0.357X_1 + 0.369X_2 + \epsilon$$

According to the results, machine learning has a significant effect on performance of commercial banks in Nairobi City County, Kenya ($\beta_1=0.357$, p value= 0.001). The relationship was considered significant since the p value 0.001 was less than the significant level of 0.05. The findings are in line with the findings of Feng, Kephart and Juarez-Colunga (2021) who indicated that there is a very strong relationship between machine learning and organization performance

The results also revealed that natural language processing has a significant effect on performance of commercial banks in Nairobi City County, Kenya ($\beta_1=0.369$, p value= 0.000). The relationship was considered significant since the p value 0.000 was less than the significant level of 0.05. The findings are in line with the findings of Lester, Manson and Semakula (2025) who

indicated that there is a very strong relationship between natural language processing and organization performance.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The study concludes that machine learning has a positive and significant effect on performance of commercial banks in Nairobi City County, Kenya. Findings revealed that response time, user adoption rate and accuracy of recommendations influence performance of commercial banks in Nairobi City County, Kenya. In addition, the study concludes that natural language processing has a positive and significant effect on performance of commercial banks in Nairobi City County, Kenya. Findings revealed that query resolution rate, language coverage and user satisfaction score influence performance of commercial banks in Nairobi City County, Kenya.

Recommendations

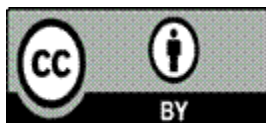
The study recommends that commercial banks in Kenya should scale up the strategic adoption of machine learning technologies across core operations such as credit risk assessment, fraud detection, and customer relationship management. By investing in advanced data analytics infrastructure, skilled personnel, and continuous model training, banks can leverage machine learning to enhance decision accuracy, reduce operational costs, and improve service personalization. In addition, the study recommends that commercial banks in Kenya should invest in the adoption and integration NLP technologies to enhance customer engagement and operational efficiency. By deploying NLP-powered tools such as chatbots, automated customer support systems, and sentiment analysis platforms, banks can provide faster, more accurate, and personalized responses to customer inquiries while reducing service costs.

REFERENCES

- Abbaspour, P. (2023). *Role of artificial intelligence and IT governance on industrial pollution management in Canada*. Retrieved From, <https://www.researchgate.net/profile/Pouya-Abbaspour/publication/>
- Adebayo, S. O., & Akinyemi, B. A. (2022). *Artificial Intelligence and ICT Management in Nigerian Financial Institutions*. *African Journal of Information Systems*, 14(2), 112–128.
- Central Bank of Kenya. (2023). *Bank Supervision Annual Report 2023*. <https://www.centralbank.go.ke>
- Chimbunde, E, Sigwadhi, L. N., & Tamuzi, J. L. (2023). *Machine learning algorithms for predicting determinants of COVID-19 mortality in South Africa*. Retrieved from file:///C:/Users/user/Downloads/
- Communications Authority of Kenya. (2022). *ICT Sector Statistical Report for Q4 2021–2022*. <https://www.ca.go.ke>

- Crowther, D. & Lancaster, G. (2018). *Research Methods: A Concise Introduction to Research in Management and Business Consultancy*. New York: Butterworth-Heinemann.
- Deloitte. (2022). *AI and the Banking Sector: Transforming Performance through Intelligence*. <https://www2.deloitte.com>
- Feng, C, Kephart, G., & Juarez-Colunga, E. (2021). Predicting COVID-19 mortality risk in Toronto, Canada: a comparison of tree-based and regression-based machine learning methods. *BMC Medical Research Methodology*, 21(267), 1-14
- Katsuki, M, Narita, N., & Matsumori, Y. (2020). Preliminary development of a deep learning-based automated primary headache diagnosis model using Japanese natural language processing of medical questionnaire. *Surgical Neurology International*, 11(475), 1-6
- Kenya Institute for Public Policy Research and Analysis (KIPPRA). (2022). *Digital Readiness and the Adoption of Emerging Technologies in Kenya*. <https://www.kippira.or.ke>
- Kimutai, H., & Muchelule, Y. (2025). Integration of artificial intelligence and performance of broadcasting companies in Nairobi City County, Kenya. *International Journal of Management and Business Research*, 7(1), 474-491.
- Kituku, B, Nganga, W., & Muchemi, L. (2021). *Leveraging on cross linguistic similarities to reduce grammar development effort for the under-resourced languages: a case of Kenyan Bantu languages*. Retrieved from <https://repository.dkut.ac.ke:8080/xmlui/>
- Munga, C. (2024). *Artificial Intelligence integration and business management metrics in the telecommunication sector in Kenya*. Retrieved From, <http://repository.kcau.ac.ke:8080/bitstream/handle/>
- Muriu, P. (2016). *Mobile based expert system model for animal health monitoring : cows disease monitoring in Kenya*. Retrieved from <http://su-plus.strathmore.edu/handle/11071/4853>
- Mwangi, J. (2024). Analyzing the role of artificial intelligence and machine learning in optimizing supply chain processes in Kenya. *International Journal of Supply Chain Management*, 9(1), 39-50
- Mziray, E. J., & Author, J. (2023). Effectiveness of information systems on automation of business processes for nonprofit organizations in Nairobi city. *European Journal of Theoretical and Applied Sciences*, 1(5), 1147-1154
- Otundo, M. R. (2024). *Robotic Process Automation (RPA) and AI: an empirical analysis in Kenya*. Retrieved from file:///C:/Users/user/Downloads/
- Pair, E, Vicas, N., & Weber, A. M. (2021). *Quantification of gender bias and sentiment toward political leaders over 20 years of Kenyan news using natural language processing*. Retrieved from file:///C:/Users/user/Downloads/
- Punjab Information Technology Board. (2022). *Annual Report on AI and ICT Management in Pakistan*. <https://www.pitb.gov.pk>

- Salim, M. M. H. M. (2024). *The impact of Artificial Intelligence acceptance on customer satisfaction in the telecommunication industry in Egypt*. Retrieved From, <https://journals.ekb.eg/article>
- Sauer, J, Overos, H., & Newlands, J. (2022). *Analyzing multilingual discussions of the standard gauge railway project in Kenya using natural language processing and social media analysis*. Retrieved from <https://apps.dtic.mil/sti/trecms/pdf/>
- Sobczak, A. (2021). Robotic process automation implementation, deployment approaches and success factors – an empirical study in Canada. *Entrepreneurship and Sustainability Issues*, 8(4), 122-147
- State Council of China. (2022). *New Generation Artificial Intelligence Development Plan*. <https://www.gov.cn>
- Stevens, W. (2023). Robotic process automation in supply chain in South Africa. *European Journal of Supply Chain Management*, 1(1), 1-10
- Turyamushanga, L. (2023). *Accounting expert systems and financial performance in Rwanda*. Retrieved from <https://irbackend.kiu.ac.ug/server/>
- Uganda Communications Commission. (2022). *ICT Development and Emerging Technologies in Uganda*. <https://www.ucc.co.ug>
- Wanjohi, N., & Waithaka, S. (2024). Information expert systems and performance of insurance firms in Nairobi County, Kenya. *International Journal of Technology and Systems*, 9(2), 1–20
- Zeng, Y., Lu, E., & Huangfu, C. (2022). *Artificial Intelligence in Chinese Financial Services: A Review*. *Journal of Asian Finance, Economics and Business*, 9(4), 87–98.



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